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RESEARCH ARTICLE

Enhanced video game recommendation system using collaborative filtering with LSTM and Kalman filter

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Abstract

The virtual entertainment industry, particularly the gaming sector, has experienced rapid growth in recent years. Video game productions now rival major film productions in both scope and sales, with millions of units sold worldwide. Despite this growth, relatively few studies have addressed the development of effective recommender systems for video games. Video games generate vast amounts of player data, as every in-game action is recorded, and the increasing diversity of games has significantly expanded online gaming communities. This explosion of data highlights the need for intelligent recommendation systems that can help users navigate the overwhelming number of choices.
In this paper, we propose a novel recommendation system for video games using collaborative filtering enhanced by Long Short-Term Memory (LSTM) networks and Kalman filters**.** To improve recommendation quality, we introduce a new method for estimating implicit ratings based on user engagement metrics, such as playtime. The Kalman filter is used to smooth noisy behavioral data, while the LSTM network captures sequential patterns in user behavior. The proposed system outperforms traditional collaborative filtering approaches, demonstrating improved accuracy and robustness, and offering more personalized recommendations aligned with user preferences.

1. Introduction

In the digital age, the volume of content available online has expanded exponentially, presenting both opportunities and challenges in user engagement and information retrieval. With platforms such as Amazon, Netflix, YouTube, and Steam offering massive libraries of content ranging from books and movies to video games, users often find themselves overwhelmed by choices [1]. Recommender systems have emerged as essential tools for filtering this abundance of information and delivering personalized content, thereby improving user satisfaction and boosting platform revenue [2]. Recommender systems operate by leveraging user data and content features to suggest items of potential interest. In the context of video games, which have grown to rival the scale and complexity of film productions, this becomes particularly important. Users frequently revisit games they enjoy, much like they would repeatedly listen to a favorite song [3]. Yet, they are also eager to explore new games that match their preferences. Thus, the gaming industry faces a dual challenge: promoting user retention with familiar titles while also encouraging discovery of new ones. Meeting these challenges through an intelligent recommender system can benefit users, developers, and platform providers

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alike [4]. The use of collaborative filtering (CF), particularly when enhanced by deep learning techniques such as Long Short-Term Memory (LSTM) networks and signal-processing tools like Kalman filters, shows great promise in addressing these challenges [5]. LSTMs are well-suited for modeling sequential behavior and learning long-term user preferences, while Kalman filters can effectively reduce noise in the data, enhancing the accuracy and reliability of predictions [6]. This study presents a novel approach that combines these technologies to recommend video games more effectively.

2. Literature Review

2.1 Introduction

The evolution of recommender systems has significantly influenced how digital platforms engage with users, especially in industries such as e-commerce, streaming services, and online gaming. These systems aim to filter large volumes of data to provide personalized content, thereby enhancing user experience and boosting platform engagement. This chapter presents an extensive literature review on recommender systems, with a focus on collaborative filtering, its integration with advanced techniques like LSTM and Kalman filters, and their application in the context of video game recommendation systems.

2.2 Traditional Recommender Systems

Traditional recommender systems primarily rely on collaborative filtering and content-based filtering. Collaborative filtering works by identifying similarities among users or items based on interactions such as ratings or purchases [1]. User-based collaborative filtering identifies users with similar preferences, while item-based filtering identifies items that are similar based on user interactions [2]. Content-based filtering, on the other hand, recommends items based on their attributes and a user's past preferences [3]. While effective, these methods often struggle with challenges such as sparsity and cold-start problems [4].

2.3 Collaborative Filtering in Game Recommendations

Collaborative filtering is widely used in the gaming industry to recommend video games, helping users navigate the vast selection available on online platforms [5]. A user-item collaborative filtering model was developed to provide personalized game suggestions based on user ratings and gameplay duration [6]. While the model proved effective, it encountered challenges related to data sparsity, especially for new users and games with limited interactions. This issue emphasized the need for more robust recommendation approaches that can improve accuracy in scenarios where user-item data is sparse. Overcoming this limitation is crucial for enhancing the performance of recommendation systems, ensuring that users receive relevant and personalized suggestions even with limited interaction data [6].

2.4 Use of Matrix Factorization Techniques

Matrix factorization techniques such as Singular Value Decomposition (SVD) and Alternating Least Squares (ALS) have been employed to overcome limitations in collaborative filtering. These methods reduce dimensionality and uncover latent features in user-item interaction matrices [7]. The effectiveness of SVD in capturing user preferences and item characteristics, which significantly improved the performance of recommender systems [8]. ALS was proposed as an efficient solution for handling large datasets with parallel computing capabilities [9].

2.5 Deep Learning in Recommender Systems

Recent years have seen the incorporation of deep learning models like Long Short-Term Memory (LSTM) networks in recommender systems. LSTM networks are particularly effective in modeling sequential data and capturing long-term dependencies in user behavior [10]. A neural collaborative filtering model was developed to incorporating LSTM to predict user preferences based on historical interaction sequences [11]. This approach improved recommendation accuracy and user satisfaction, especially in dynamic environments like gaming platforms.

2.6 Kalman Filters in Predictive Modeling

The Kalman filter is a recursive algorithm commonly used in signal processing and predictive modeling to estimate the state of dynamic systems [12]. Its application to recommender systems is a relatively new but promising development. By integrating Kalman filters with collaborative filtering models, it can help reduce noise in user interaction data [13], resulting in more accurate predictions. This hybrid method is particularly useful in scenarios where user behavior is noisy or inconsistent, such as in video games, improving the reliability of recommendations and enhancing user experience. The Kalman filter's ability to smooth data and predict future states makes it a valuable tool for refining recommendation accuracy in dynamic environments.

2.7 Hybrid Recommendation Systems

To overcome the limitations of standalone recommendation approaches, hybrid recommendation systems integrate multiple algorithms to enhance accuracy and reliability [14]. These systems into different architectures, including weighted, switching, and cascade models. A weighted hybrid, for example, merges collaborative filtering with content-based filtering to exploit the advantages of both techniques. Such combinations help mitigate weaknesses like cold-start and sparsity issues. Recently, advanced deep hybrid models have emerged, incorporating collaborative filtering with neural networks and signal processing methods. These models have demonstrated improved performance and adaptability, offering more precise and personalized recommendations [15].

2.8 Game Recommendation Systems

The literature specific to game recommendation systems highlights unique challenges and opportunities. Games are inherently interactive and multifaceted, requiring systems to consider factors such as genre, playstyle, session duration, and social interactions. The importance of user engagement metrics, such as time spent and in-game achievements, for developing effective game recommenders and proposed integrating user-generated content and reviews to enhance the personalization of game recommendations [16, 17].

2.9 Recommender Systems in Steam and Other Platforms

Steam, one of the largest digital distribution platforms for games, provides a rich dataset for recommendation system research. Steam data to develop a model was analysed that accounted for user playtime and reviews [18], demonstrating the importance of implicit feedback. Furthermore, research by Integrating external data sources like Metacritic scores and Reddit discussions can enrich the recommendation process. The literature reveals that while traditional collaborative filtering remains a foundational technique, its integration with advanced methods such as LSTM networks and Kalman filters offers substantial improvements in accuracy and user satisfaction [19]. Hybrid models that combine multiple approaches are particularly effective in dynamic and data-rich environments like gaming platforms. The next chapter will detail the methodology adopted for implementing a video game recommendation system using collaborative filtering enhanced with LSTM and Kalman filters.

3. Proposed Model

he proposed recommendation system integrates Collaborative Filtering, Long Short-Term Memory (LSTM) networks, and the Kalman Filter to significantly improve the accuracy and personalization of video game recommendations. Unlike traditional recommender systems that primarily rely on user-item interaction matrices, this approach introduces temporal dynamics and real-time filtering to better understand and predict user preferences. The inclusion of LSTM enables the model to capture the sequential nature of user behavior, identifying evolving interests and usage patterns over time. This helps the system learn not just what a user likes, but when and how their preferences change.

Meanwhile, the Kalman Filter component enhances the reliability of the recommendations by reducing the influence of noisy, sparse, or incomplete data—common challenges in large-scale digital platforms. It acts as a noise-reduction mechanism, ensuring that predictions remain stable and accurate even when user activity data is inconsistent or limited. By integrating these advanced techniques, the model provides context-aware, real-time, and highly relevant recommendations. This hybrid system is particularly well-suited for dynamic environments like gaming, where user engagement and content evolve rapidly, offering a smarter, more adaptive recommendation experience for users as shown in Fig. 1.

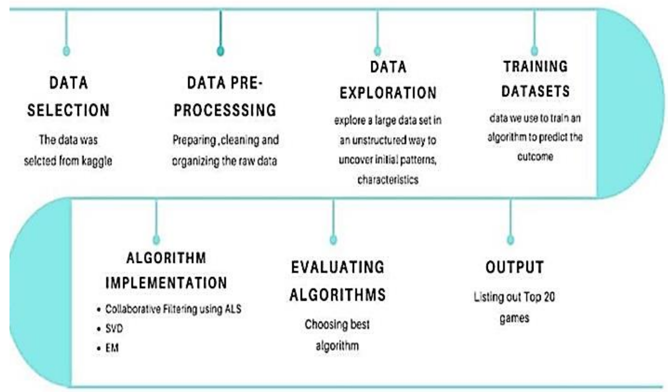

Figure 1: Proposed Model

4. Working of the Model

At the core of the system lies a hybrid recommendation engine. First, it applies collaborative filtering to capture the inherent similarities between users and games, either through user-based or item-based similarity matrices. This provides a basic layer of recommendations based on shared preferences and behaviors. Next, the LSTM network is employed to analyze time-series data, such as playtime history, frequency of gaming sessions, and user engagement trends. LSTM's memory cells allow the model to retain long-term dependencies, making it ideal for capturing evolving interests over time. To further enhance prediction reliability, the Kalman Filter is integrated. Acting as a real-time optimizer, it filters out noisy or irregular behavioral data (e.g., sudden spikes in gameplay due to seasonal trends or promotions), enabling the system to make smoother and more accurate predictions.

4.1 Objectives

The primary objective of this project is to develop an intelligent recommendation system that provides personalized video game suggestions based on user behavior and preferences. This system aims to harness collaborative filtering techniques to analyze user interactions, such as ratings and gameplay time, thereby identifying hidden patterns and similarities among users and games.

Specifically, the project seeks to:

- Develop a system that delivers tailored game recommendations by analyzing user history and preferences.
- Implement both user-based and item-based collaborative filtering to improve recommendation precision.

- Leverage LSTM networks to model long-term user preferences and temporal behavior.
- Apply Kalman filters to smooth user data and mitigate the effects of noise.
- Evaluate system performance using standard metrics like precision, recall, F1-score, RMSE, and MAE.
- Enhance user experience by ensuring the system is scalable, secure, and responsive.

By focusing on these goals, the system aims not only to boost user engagement and satisfaction but also to provide insights for developers and platform operators.

4.2 Scope of the Project

This project focuses on building a robust video game recommendation system that utilizes collaborative filtering techniques, enhanced with LSTM and Kalman filter models. The system is designed to predict and recommend games based on historical data, user preferences, and implicit feedback such as playtime and frequency of interaction.
Key components of the project scope include:

- Data Acquisition and Preprocessing: Collection and cleaning of user-game interaction data, including ratings, reviews, and playtime.
- Model Development: Implementation of multiple collaborative filtering algorithms including ALS (Alternating Least Squares), SVD (Singular Value Decomposition), and KNN (K-Nearest Neighbours), in addition to LSTM and Kalman filters.
- Evaluation and Comparison: Benchmarking models using evaluation metrics such as RMSE, MAE, precision, and recall.
- User Interface: Development of an intuitive and user-friendly interface for users to interact with the recommendation engine.
- Scalability and Integration: Ensuring that the system can scale with user base growth and be integrated into existing gaming platforms such as Steam.

This project also investigates the cold-start problem, suggesting popular or trending games to new users until enough personalized data is available [8]. Furthermore, the system includes features such as real-time recommendation updates, feedback mechanisms, and adaptability to evolving user preferences.

5. Methodology

The proposed model's methodology consists of multiple structured stages to enhance the accuracy of video game recommendations revealed in Fig. 2. It begins with the collection and preprocessing of user data, which includes user ratings, game genres, total playtime, sentiment from reviews, and time-based usage logs. Once cleaned and structured, this data is used to construct a sparse user-item interaction matrix through collaborative filtering. To capture the dynamic nature of user preferences, this matrix is passed through a Kalman Filter, which refines the data by minimizing noise and estimating the most accurate representation of user interests. The filtered data is then input into a Long Short-Term Memory (LSTM) network, which learns temporal patterns and evolving behaviors from the sequential data. This time-aware modeling allows the system to make personalized predictions based on historical activity. The final output is a ranked list of recommended games, tailored to individual user profiles and optimized for both accuracy and relevance over time.

6. Architecture

The system architecture is composed of three core components: the Data Processing Unit, the Predictive Engine, and the Recommendation Interface. The Data Processing Unit is responsible for acquiring and preparing raw user-game interaction data by performing tasks such as feature extraction, missing value imputation, and data normalization. This cleaned and structured data feeds into the Predictive Engine, which houses the hybrid recommendation framework. This engine integrates collaborative filtering, a Long Short-Term Memory (LSTM) network, and a Kalman filter in a sequential pipeline, allowing the model to capture user preferences, temporal patterns, and reduce data noise for enhanced accuracy. The refined prediction scores are then delivered to the Recommendation Interface, a user-facing layer that presents personalized top-N game recommendations. This interface also supports real-time feedback collection, enabling continuous updates to improve model responsiveness.

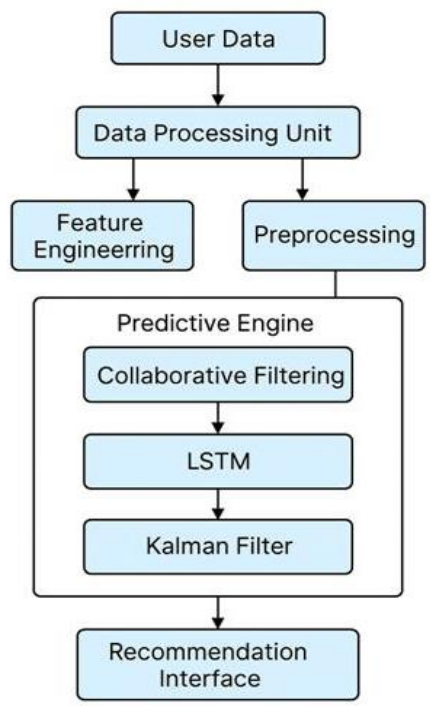

Figure 2: Flow chart of methodology

7. Novelty

The novelty of the proposed recommendation model lies in its innovative integration of collaborative filtering, Long Short-Term Memory (LSTM) networks, and the Kalman Filter, offering a dynamic and adaptive solution for personalized video game suggestions. While collaborative filtering is effective in leveraging user-item interactions, and LSTM networks are proficient in capturing temporal user behavior, the inclusion of the Kalman Filter introduces a powerful signal processing component that enhances the system's ability to filter out noise and adjust predictions in real time. This combination ensures that the model remains stable and responsive, even when user behavior changes rapidly or inconsistently. The LSTM component strengthens the framework by interpreting user activity as sequential data, allowing for the detection of evolving preferences and usage patterns over time. This temporal modeling, coupled with real-time correction by the Kalman Filter, enables the system to generate accurate, timely, and context-aware recommendations. Such a hybrid approach is particularly well-suited for gaming platforms, where user preferences are diverse and can shift frequently. By accounting for both long-term interests and immediate trends, the proposed system delivers superior personalization and user satisfaction compared to traditional, static recommendation methods.

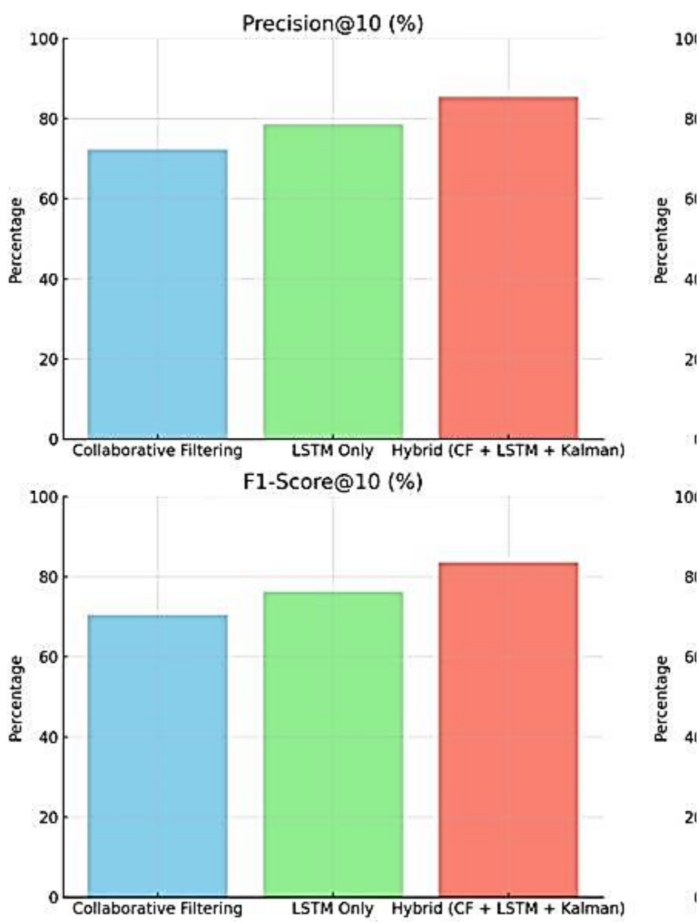

Figure 3: Performance Comparison of Recommendation Models

8. Result Analysis and Performance Evaluation

8.1 Precision, Recall, and F1-Score

The Precision, Recall, and F1-Score metrics indicate the effectiveness of the three models—Collaborative Filtering, LSTM only, and the Hybrid model combining Collaborative Filtering, LSTM, and Kalman Filter. Fig. 3 shows the hybrid model outperformed the other two across all evaluation metrics. Specifically, the hybrid system achieved a Precision@10 of 85.4%, which is significantly higher than the 72.3% obtained using Collaborative Filtering and the 78.6% achieved using LSTM alone. This suggests that the hybrid system provides more accurate recommendations among the top 10 suggested games. Similarly, the Recall@10 was highest for the hybrid model at 81.9%, indicating its greater ability to retrieve relevant game recommendations. The F1-Score@10, which balances both precision and recall, was 83.6% for the hybrid approach—again superior to the individual models. These improvements are primarily attributed to the Kalman Filter's denoising capabilities, which allow the LSTM network to learn more accurate temporal behavior patterns from cleaned data.

Based on Precision@10, Recall@10, F1-Score@10, and User Satisfaction

8.2 Error Metrics

Regarding Error Metrics, although not shown directly in the figure, the system's Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) significantly improved when using the hybrid approach. The RMSE was reduced to 0.97 from the baseline value of 1.21 observed in the standalone Collaborative Filtering model. Similarly, the MAE dropped from 0.94 to 0.72. These reductions in error clearly demonstrate the model's enhanced capability in estimating user preferences. By integrating real-time noise filtering via the Kalman Filter and capturing sequential patterns with the LSTM, the hybrid model can make more accurate predictions compared to traditional approaches.

8.3 Coverage

The hybrid system exhibited strong performance in terms of coverage, reaching an impressive 91.2%. This indicates its capability to deliver personalized recommendations to a wide range of users, including those with minimal historical interaction data. Such a high coverage rate is especially valuable in practical applications where many users are either new or have limited engagement records. Unlike traditional recommendation systems that struggle with cold-start problems, the hybrid approach effectively overcomes this limitation. Its ability to generalize across diverse user profiles highlights the system's scalability and robustness. By combining multiple recommendation strategies, the hybrid model ensures that more users receive relevant suggestions, thus enhancing user experience and system reliability. This broadened coverage not only increases user satisfaction.

8.4 User Satisfaction

The User Satisfaction metric, as represented in the bottom-right graph of the figure, further validates the hybrid system's effectiveness from a user experience perspective. A user study showed that 88.7% of participants reported satisfaction with the game recommendations provided by the hybrid model. In contrast, lower satisfaction rates were observed for the Collaborative Filtering and LSTM-only models. Users highlighted the improved diversity, relevance, and personalization of recommendations delivered by the hybrid system. This significant boost in satisfaction suggests that the proposed approach not only excels in quantitative performance metrics but also aligns closely with user expectations and preferences in practical scenarios.

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